Development Trend Analysis of the Research on Recommendation System

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Recommendation systems are widely used to help deal with the problem of information overload. Over the past decades, a variety of recommendation systems have been developed as the amount of information in the world increases far more quickly than our ability to process it. This paper aims to analyze existing developed recommendation systems, provide systemic review, and present some basic issues on improvement action. Through this, we also suggest useful implications for better recommendation systems and give some ideas to recommendation system developers to improve their system. Especially, this study focuses on researches on recommendation system. In our research, we analyze the studies along with four different keys dimensions : their domain, objective, underlying model, and evaluation method of recommendation systems and portray the results as statistics or statistical graphics or table form.

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1. Introduction

Over the past decades, recommendation systems have attracted widespread attention for two broad causes. First, a variety of recommendation systems have been developed as the World-Wide-Web continues to grow explosively. Through the Internet, the amount of information in the world is increasing far more quickly than our ability to process it. This vast amount of available information spurs the development of systems that filter out irrelevant information and then select items that meet user needs. Second, the emergence of e-commerce has also led to the development of recommendation systems. Recommendation systems enrich on-line shop sales and help to increase customer satisfaction and customer loyalty. They have been widely used in many applications to suggest products, services, and information items to potential consumers. Recommen-

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dation systems have become an important part of many e-commerce services, for instance, amazon.com (http://www.amazon.com/) and its subsidiary CDNow (http://www.cdnow.com/).

The study and development of recommendation systems is a very active field of research and this system has been used in a variety of objectives, for example :

- enhance user satisfaction and loyalty (e.g., Kumar, R. et al., 2001; Vucetic, S. and Obradovic, Z, 2005).
- overcome the information overload (e.g., Changchien, S. W. and Lu, T. C., 2001; Li, Y. et al., 2005).
- assist customers in choosing products or services they might be interested in (e.g., Knuchel, J. P. and Stojanovic, N., 2006; Sakamoto, T., 2007; Shahabi, C. and Chen, Y., 2003).
- help enterprises launch one-to-one marketing (e.g., Hung, L. P., 2005; Min, S. and Han, I., 2005).
- make predictions concerning users' interest on unobserved items and present unexpected items (e.g., Chen, C., 2004; Jian, C., 2005; Kamahara, J., 2005; Lekakos, G. and Giaglis, G. M., 2006).

While applications of recommendation system are diverse, two broad categories emerge. One only focuses on a specific domain issue, and the other tries to improve performance and overcome shortcomings of the recommendation system itself by proposing new recommendation methods. Our research focuses on this second type.

Our research goal is to analyze existing developed recommendation systems and to provide systemic review and to present some basic issues on improvement action. Through this, we also find useful implications on recommendation system and give some ideas to recommendation system developers to improve their system.

This paper first defines the boundaries of the analysis - that is, by specifying what research falls within or is outside of its scope, and we describe how we collect the papers. Then we analyze the studies that form the central data of our analysis. Finally, we present a set of implications, an agenda for future research and conclusions.

2. The scope of the analysis

As significant academic interest has been devoted to recommendation system-related research issues, numerous papers are published in this field. So we define in the scope of our meta-analysis that relevant studies must be grounded in both information systems and computer science fields.

In developing our research, we used three ways to collect the papers. First we used the National Digital Science Library (NDSL) system, which is the biggest journal indexing database for a scientific research in Korea. The database provides 62,704 journals and 194,534 proceedings. It also provides 22,571,483 full-text articles itself - from 22,813 journals and 8,180 proceedings, respectively- and provides 41,079,468 links within the citation/abstract records to the electronic version of the publication. Secondly, we performed hand searching of key journals in both information systems and computer science fields such as Decision Support Systems, Decision Science, Expert System, Management Science, Expert Systems with Applications, IEEE Intelligent Systems, IEEE Computer Science, and etc. Finally, we checked the reference lists of the papers.

Our recent search on the NDSL resulted in around 486 papers on recommendation systems in both journal publications and conference articles from 1997 through 2008. A similar result from a hand search revealed that close to 83 papers were published on recommendation systems without a time condition.

Among them, we selected the papers which were grounded in both information system and computer science fields and only focused on recommendation systems. Then, we excluded the simple application papers that just focused on a specific domain issue and had no novel contribution in terms of a recommendation system. Afterwards, we added some relevant papers which were obtained by checking reference lists. Finally, for the study quality, we confirmed our list with a double-blind method. As a result, we selected 85 papers for our meta-analysis. <Table 1> presents the reference disciplines examined in this research, together with literature support for those categories.

<Table 1> Reference Disciplines

Discipline	Key References	Explanations/definitions of additional categories
Computer science		Researchers focus on using specific technology.
Database	Shahabi and Chen, 2003	
Artificial intelligence	Yukawa, 2001; Rafter and Smyth, 2005	
Agent	Abe, 2000; Lee et al., 2002; Symeonidis et al., 2003; Xiao et al., 2003; Lee, 2004, 2005; Salter and Antonopoulos, 2006; Walter et al., 2007	
Management information system		Researchers cite prior IT studies as the source of their methodologis.
Data mining	Lawrence et al., 2001; Schafer et al., 2001; Symeonidis et al., 2003; Hsieh et al., 2004	
Information science	Cornelis et al., 2007	
Informatino system	Perugini et al., 2004; Chen and Chen, 2005; Vucetic and Obradovic, 2005; Dubois et al., 2006; Kim, 2006	
Other		A paper relied on a reference discipline other than one of those specified, such as marketing, (see (Yuan and Cheng, 2004)).
Not applicable		A paper either relied on a number of reference disciplines, none of which was dominant, or it did not rely on a reference discipline (see (Chen et al., 2008)).

<Table 2> Motivation for Addressing the Five Diversity Characteristics and Research Questions

Diversity dimension	Key points	Research questions addressed
Reference discipline	Recommender systems are successful in domains such as books, TV program and news articles (Lekakos and Caravelas, 2008)	Research Question 1 : What kind of domain is applied?
	Improvement of the algorithm and combined applications of traditional recommendation system are major concerns (Weng et al., 2007)	Research Question 2 : What is the underlying objective?
	Recommendation systems have been developed various methods to predict their user's preferences (Kim et al., 2002)	Research Question 3 : What is the underlying recommendation method?
	Several factors have impacts on the performance of the recommendation method. (Wang and Shao, 2004)	Research Question 4 : How is the recommendation system evaluated?

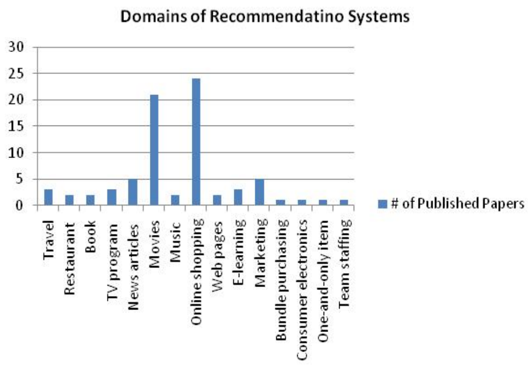
Based on the current efforts as summarized in <Table 2>, we established four main research questions. In light of the answers to these questions, the results are visualized as statistics, statistical graphics or table forms. Toward that end, several directions for a future recommendation system are suggested.

3. Development Trend of Recommendation Systems

3.1 Domains of recommendation systems

Generally, recommendation systems are used to recommend items that users may be interested in based on users' predefined preferences or users' historic data. These systems have been applied to both physical and information items. A number of related prototypes have been developed for recommending items such as travel, restaurants, books, TV programs, news articles, movies, music, web pages, e-learning contents, and many more as listed in <Table 1>.

And <Figure 1> graphs the number of published papers by their domain. It shows the most popular domain of recommendation systems is online shopping and indicates many papers belong to the movie domain, with other domains evenly distributed. However, some studies just discussed their algorithm or framework without any application.



<Figure 1> Summary of Published Papers by Domain

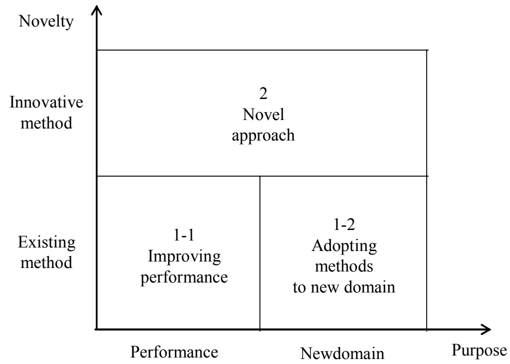
The number of papers in the online shopping domain could be explained by the growth of e-commerce, whereas the papers in a movie domain might be led by the usability of collecting experimental data. Movie-related data is relatively easy to get from several open databases such as the MovieLens system (http://movielens.umn.edu/) and EachMovie Database (http://www.imdb.com/).

<Table 3> Domains of Recommendation Systems

Domain	Study
Travel	Huang and Bian, 2007
Restaurants	Sakamoto et al., 2007
Books	Kim and Ko et al., 2004
TV programs	Tsunoda and Hoshino, 2007
News Articles	Lee and Park, 2007; Hsieh et al., 2004
Movies	Chen et al., 2008; Lekakos and Caravelas, 2008; Li et al., 2005
Music	Chen and Chen, 2005; Hayes and Cunningham, 2004
Online shopping	Kim et al., 2005; Xiao et al., 2003; Zhang and Jiao, 2007
Web pages	Ishikawa et al., 2002
E-learning contents	Cho et al., 2007; Wang and Shao, 2004
Marketing	Yuan and Cheng, 2004
Bundle purchasing	Garfinkel et al., 2006
Consumer electronics	Cao and Li, 2007
One-and-only item	Cornelis et al., 2007
Team staffing	Malinowski et al., 2007

3.2 Underlying Objectives of Recommendation Systems

As recommendation systems have been developed for many years, there are many studies in this field. We classified their underlying objectives into three categories as in <Figure 2>.



<Figure 2> Objectives of Published Papers

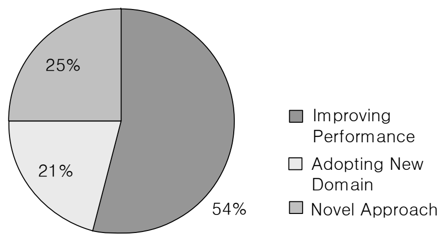
Each dimension means as follows.

1-1 : Improving performance : The goal is to improve performance of conventional recommendation systems in current domains by adjusting and complementing existing methods.

1-2 : Adopting methods to new domain : The goal is to adopt existing methods to a new domain.

2 : Novel approach : The goal is to propose an innovative method for recommendation systems regardless of domain.

Based on the dimension of objectives, we analyzed the underlying objective of the published papers.



<Figure 3> Summary of Published Papers by Underlying Objectives

<Figure 3> shows the result. The majority of the studies focus on improving performance of conventional recommendation systems, proposing ways to adjust or complete existing methods for better performance. The rate of adopting methods to new domain and novel approach were revealed at similar rates. There were many studies for improving performance. Besides, not a few elaborations have been done to introduce a novel technique for both objectives- increasing performances and extending recommendation systems to new domains.

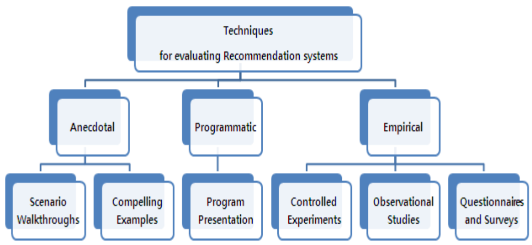
3.3 Underlying Methods of Recommendation Systems

The heart of a recommendation system is its recommendation-making algorithm. Researchers and practitioners have investigated and experimented with a variety of recommendation approaches. <Tables 2>, <Tables 3> and <Tables 4> provide classifications of the underlying methods in an improving performance dimension, adopting methods to new domain dimension, and novel approach dimension, respectively.

First, recommendation systems in improving performance dimension mainly aim to propose the way to address drawbacks of collaborative filtering or content based filtering-which is the most representative method for recommendation. And they also try to improve certain recommendation system itself through suggesting alternatives to overcome its shortcoming and redesign data source used for recommendation such as user requirement and historical preference of user. Second, researches in adopting methods to new domain dimension propose new recommendation systems applied existing recommendation methods to new area such as specific user group, specific item or content, marketing campaign, mobile environment, peer to peer Architecture and team staffing. Lastly, creative approaches are introduced to develop recommendation system in novel approach dimension. For example, they use emerging technologies such as web technology and ubiquitous technology or user behavioral model such as Technology Acceptance Model (TAM).

3.4 Methods of Evaluation of Recommendation Systems

This research applies a technique classification for studying effectiveness (Hundhausen, 1996) of analyzing the evaluation method of the proposed recommendation system. All of the papers considered in our study make use of one or more the techniques presented in <Figure 4>.



<Figure 4> Techniques for evaluating the recommendation system

Scenario walkthroughs describe the use of a system under a hypothetical, but highly plausible, set of circumstances. In order to highlight actual instances in which their system clearly succeeded in assisting its users, authors of system papers present

<Table 4> Classification of underlying method to improve performance dimension

Aspect	Category	Drawback	Underlying method
Recommendation method	Collaborative Filtering	Sparsity problem (Content-less problem)	◦ Community-based approach (hybrid (CBF + CF) + clustering). ◦ Build a model for preference prediction by using association rule mining. ◦ Construct pseudo rating matrix from the implicit feedback data. ◦ Use an implicit users' relevance feedback. ◦ Web usage mining-driven CF. ◦ Automatic rating based on user's clickstream data. ◦ Capture the user's current context. ◦ Use customer demands as valuable content information. ◦ Apply the concept of lifestyle. ◦ Document relationship mining from logs and Spreading Activation recommendations. ◦ Latent class model (LCM).
		Scalability problem	◦ Product taxonomy to improve the performance of searching for nearest neighbors through dimensionality reduction of the rating database. ◦ Nearest-neighbor CF algorithms through a model-based approach (latent semantic indexing (LSI)).
		Cold-start problem (new product problem, first-rater problem)	◦ Incorporate the feedback of users. ◦ Feature-based RS : analyze purchasing behaviors based on product features from transaction records and product feature databases.
		Stability-Plasticity dilemma	◦ Web mining (neural network based on ART2) + K-means clustering.
		No interaction	◦ Uses data mining techniques and fuzzy logic ◦ Conversational collaborative recommendation.
		High latency in given predictions	◦ A regression-based approach that first learns a number of experts describing relationships in ratings between pairs of items.
	Content Based Filtering	Feature selection problem	◦ Use of the support vector machine (SVM).
		Simple matching	◦ Semantic-expansion approach (semantic networks + spreading activation model)
Recommendation system	Group	No consideration of the interaction of group members	◦ A hybrid approach (collaborative filtering + GA) to predict unknown group ratings based on the known ratings.
	Frequency-based	The lack of personalization	◦ A trust-based recommendation : agents use users' social network.

Recommendation system	Knowledge-based	Update knowledge base	◦ A hybrid approach (knowledge-based recommendation + learning component).
	Association rules-based	Dealing with transaction database repeatedly	◦ Build the customer shopping model based on Bayesian networks.
	Web-based	Time consuming	◦ Hierarchical classifying techniques + data mining on the category tree. ◦ Using the moving average rule.
	User modeling	Without considering different access intentions	◦ Use models of both user preferences and the user's intentional context.
Source of recommendation	User requirement	Represent in a precise form	◦ A rational recommendation method : agents judge the rationality of items to be recommended, Use a multi-attribute utility function.
		Heterogeneous customer requirement	◦ Knowledge discovery techniques. ◦ Requirement preprocessing-semantic analysis : adopt pre-defined formats to describe the customer requirements.
	historical preference of user	Numerical scale expression	◦ Analytic Hierarchy Process (AHP) for ranking user's attraction. ◦ Offer a multigranular linguistic context. ◦ The preference of each user is expressed by multiple ranked lists of items.
		Binary type data	◦ Hybrid (CBF + CF) + one-to-five scale rating. ◦ Use the navigational and behavioral patterns of customers to estimate the preference levels of a customer for the products which are clicked but not purchased.
		Basis solely on historical rating data (no current information)	◦ Task-focused approach. ◦ Use conversational, preference-based feedback. ◦ Agent-based system.
		Multiple interest and Multiple content	◦ Hybrid collaborative filtering based on item + collaborative filtering based on user.
		Changes in user interest	◦ Model-based approach : a time period of length is used to detect the purchase sequence.
		Conflicting preferences	◦ Voting theory + reasoning procedure.
		The lack of understanding	◦ Bayesian network to estimating a user's preferences.
		The lack of the way to reflect the preference	◦ Use of time-related data to reflect changes in user interest. ◦ Utility range-base algorithm, multi-attribute decision making (MADM).
		Heterogeneous info	◦ Uses ontology in OWL.
		Temporal effects	◦ Consider the temporal features of an item.

<Table 5> Classification of underlying method of adopting methods to new domain dimension

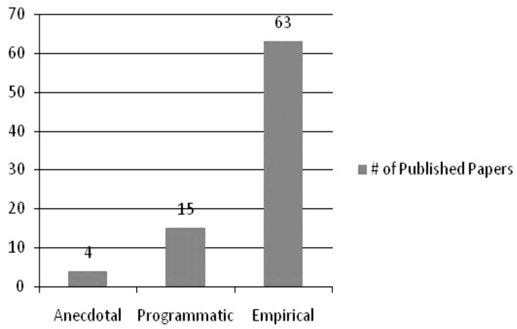
Aspect	Proposed Domain	Underlying method
Specific user group	Customers who are most likely to buy recommended products	◦ Web usage mining (DT) to minimize false positives by making recommendations.
	Customers with high profitability	◦ Multi-agent system to set different recommendation services for customers in different tiers.
Specific item (or content)	One-and-only item (which there is only one single instance)	◦ Fuzzy logic which allows a reflection of the graded/uncertain information in the domain.
	High-involvement and knowledge-intensive domains	◦ Source diversity, heterogeneous source receptivity : Dual recommendation groups-a similar users' group and an expert-users' group-as credible information sources.
	Use consumer product reviews	◦ Text-mining techniques.
Marketing campaign	One-to-one marketing for online retailers	◦ A modified product taxonomy and customer classification to identify customers' shopping behavior : product addictive, brand addictive or a hybrid addictive.
	Customer service and marketing analysis tools in e-commerce website	◦ Hybrid : an intelligent agent based on case-based reasoning and CF.
	Bundle purchasing	◦ Hybrid + considering product price and savings as an important factor.
	Acquiring and revising user preference in mobile recommendation system	◦ Limited asking and answering of questions based mostly on critiques : the user can critique a system recommendation at each cycle.
Mobile environment	Mobility-aware recommendation system	◦ Use location information of a mobile user (Locality-based recommendation).
	Context-sensitive recommendation	◦ Consider both the timing and context of recommendation messages.
	Contextualized mobile advertising	◦ Combination of two-level neural network learning.
	Heterogeneous product recommendation in mobile marketing	◦ Use the personalized analogy structures between the heterogeneous products and product ontology.
Peer to Peer Architecture	Recommendation system in peer to peer architecture	◦ Personal recommendation agents which reside on each peer's computer : use the recommendation agent.
Team staffing	Team staffing	◦ Incorporating recommendation systems into the relational modeling approach.

<Table 6> Classification of underlying method of Novel approach dimension

Aspect	Proposed technique	Underlying method
Emerging technique	Web technology	◦ Data gathering and usage mining technology. ◦ Constructs user models by classifying the Web access logs.
	Mobile agent technology	◦ Mobile recommendation agent to capture the customer behavior : real-time action, profile.
	Multi-agent system	◦ Multi-agent system that is capable of eliciting expert knowledge and of recommending optimal products (an agent-based DSS).
	Concept lattice	◦ A concept lattice is considered for visualizing and generating user profile rules.
	Apriori data mining algorithm	◦ Analyzes the process of discovering association rules in big repositories and of transforming them into user-adapted recommendations.
	Context-aware	◦ Context-aware recommendations are based on provided feedback, context data, and an ontology-based content categorization scheme.
	Improved Fuzzy Association Memory	◦ Re-adjusts the connection weights between the nodes of FAM using error back propagation and simplifies the fuzzy rules.
	Fuzzy approximate reasoning	◦ Offer a general framework for the recommendation process.
	Random graph theory	◦ Draw bipartite consumer-product graphs that represent sales transactions. ◦ Analyze the simulated consumer-product graphs generated by models that embed two representative recommendation algorithms (Consumer-Product Graph, Consumer Graph, and Product Graph).
	Discrete wavelet transformation	◦ A mathematically proven technique for data reduction.
	Automatic Metadata Expansion	◦ A method to enhance metadata from electronic program guide (EPG) data.
	Support Vector Machine	◦ A popular classifier method used between two classes, by adding axes of context to the feature space in order to consider the users' context.
	Time-framed navigation clustering	◦ A new clustering method to cluster users based on the time-framed navigation sessions (week, semester in e-learning).
	Extended ARG (ARG + ontology)	◦ Integrates ARG image content and semantics in the corresponding ontology, to identify and interpret the images.
	Machine learning techniques	◦ Learn the optimal user similarity measure as well as user rating styles.
User behavioral model	Technology Acceptance Model (TAM)	◦ Refines recommendation results by considering the user's needs type at the point of usage.

compelling examples of their system in use. Program presentation simply makes available for public inspection the actual programs. Controlled experiments aim to assert to a causal relationship between factors and measures. Observational studies investigate some activity of interest in an exploratory. Questionnaires and surveys elicit written responses to a set of questions in which the researcher is interested and request subjective data on their respondents' preference, opinions, and advice.

<Figure 5> graphs the number of published papers that employ each of techniques. As can be seen from figure, papers that make use of the empirical techniques outnumber the others.



<Figure 5> Summary of published papers by the evaluation techniques

We also organized the metrics for evaluating recommender systems. The result shows a large diversity of evaluation metrics in use. However, these metrics can be classified into three categories as follows.

1. Quality
2. Performance
3. Other

The quality of recommendation systems is used to measure by accuracy metrics and information retrieval metrics. Accuracy metrics measure the quality of nearness to the truth or the true value achieved by a system. The most used formulation is (1) and (2).

$$\text{Accuracy} = \frac{\text{number of good cases}}{\text{number of cases}} \quad (1)$$

$$\text{Accuracy} = \frac{\text{number of successful recommendations}}{\text{number of recommendations}} \quad (2)$$

The metric mean absolute error (MAE) is also common as accuracy metrics. This metric measures the average absolute deviation between each predicted rating P(u, i) and each user's real ones p(u, i). This derives the (3), where i must have been rated by u (to obtain p(u, i)). In this, N is the number of observations available. Several recommendation systems make use of this metric for the evaluation.

$$\mathrm{MAE} = \frac{\sum_{u,i} |p(u,i) - P(u,i)|}{N} \quad (3)$$

The representative information retrieval metrics are Precision, Recall, and F1. To evaluate the quality of the recommendation set, measures of precision and recall have been widely used in the field of recommendation systems. These are computed as follows.

$$\text{Precision} = \frac{\text{Number of hit products}}{\text{Total number of recommended products}} \quad (4)$$

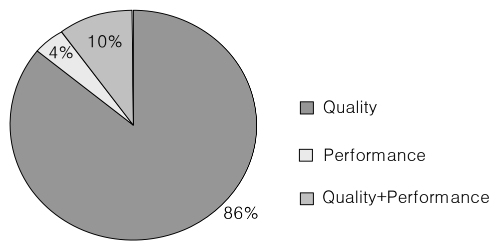
$$\text{Recall} = \frac{\text{Number of hit products}}{\text{Total number of products purchased at period T}} \quad (5)$$

$$F1 = \frac{\text{Precision x Recall}}{(\text{Precision + Recall})/2} \quad (6)$$

Some studies use the performance metrics for evaluating performance of their recommendation system. The most used and well-known metrics are both computation time and throughput. Generally, the computation time metric is computed by the response time. The response time is defined as the amount of time required to compute all recommendations, and the throughput denotes the rate at which the recommendations are computed in terms of recommendations per second.

Other systems use a user satisfaction metric. It measures the degree of matching between an item and a group of users by analyzing the preferences of a group of users and the properties of the item.

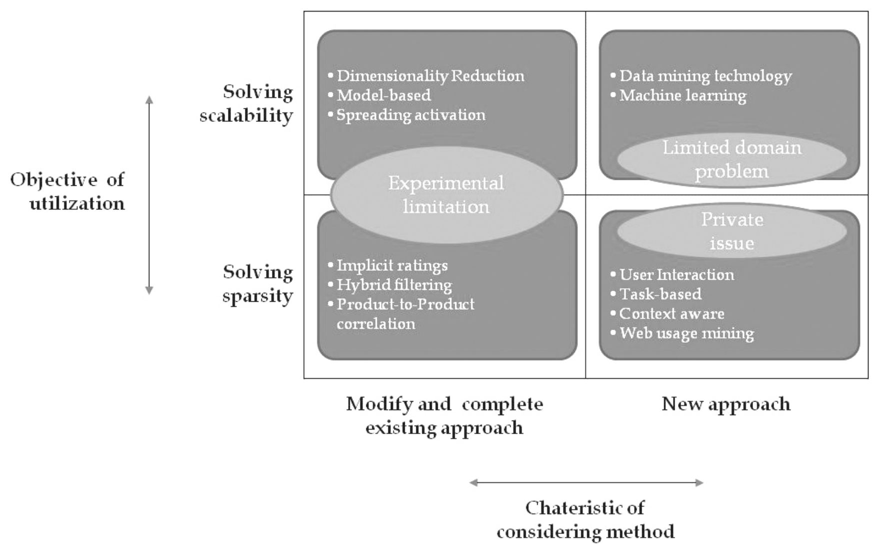
As <Figure 6> indicates, the number of published papers that use only quality metrics outnumber the others.



<Figure 6> Summary of published papers by the evaluation metrics

3.5 Limitations of Recommendation Systems

Since the recommendation systems have been developed for many years, a variety of approaches have been considered. We classified mostly used approaches with four dimensions as shown in <Figure 7> : objective of utilization and characteristics of considering method. Then we organized the limi-



<Figure 7> limitations of developed recommendation systems

tations which are explicitly referred to in the papers by the dimensions.

1. Experimental limitation (Kwak and Cho, 2001; Kim et al., 2002; Cho and Kim, 2004; Wang and Shao, 2004; Weng and Liu, 2004; Kamahara, 2005; Vucetic and Obradovic, 2005; Kim et al., 2006; Huang and Bian, 2007).
2. Limited domain problem (Herlocker and Konstan, 2001; Lee et al., 2002; Knuchel and Stojanovic, 2006; Cho et al., 2007; Liang et al., 2007).
3. Private issue (Shih et al., 2002; Kwon, 2003; Hayes and Cunningham, 2004; Oku et al., 2006; Sugano et al., 2006; Rack et al., 2006; Choi et al., 2007).

The sources of limitations in performing experiment are not identical. First, the size of sample dataset is small in comparison to real. It is to maximize the efficiency and there are difficulties to gather the real data. Second, the quality of data depends on the system that gathered the data and pre-defined formats to describe the data requirements. It may cause the absence of good data required. Third, existing approaches do not consider complete factors. They examine the various factors only partially. Although the real recommendation is influenced by more factors, most approaches can't represent various aspects of users' profiles or items. Fourth, they do not apply their proposed approaches to real-world datasets. Lastly, the experiments have many constraints and assumptions. This issue usually states in the papers which modify and complete existing approach such as model-based approach and hybrid filtering.

Most approaches develop the recommendation system in the particular domain. Hence, it needs to be applied to other domains in order to validate generalizability of the proposed approach. Some approaches require a great deal of work from professionals in the application domain. It is very crucial issue to both the approaches which incorporate some domain-specific content knowledge and the approaches are very sensitive to data's feature such as data mining technology and machine learning.

Private issue is one of the most common limitations in the approaches which use user-related information such as context-aware approach. They assume that they could collect user's contextual information without disturbing the users. However, users tend to use the recommendation system to get recommendations without providing their private information. Customer profile security and privacy concern in the e-commerce environment is getting important in e-commerce. This issue becomes a major consideration in recent years.

4. Implications

Through our analysis, we could identify several clear development trends and find five principal implications. In this section, we summary those trends briefly and derive five implications as follows.

First, today's recommendation systems are developed and adopted only in somewhat limited domains. However, as recommendation methods are advanced, those domains will continue to be expanded. Most current developed recommendation systems focus on product recommendation, making recommendation in same product category and recommendation for individual person. However, their approaches can be expanded a person or a career recommendation, making recommendation in an associated product category and recommendation for group. Moreover, rigorous efforts to propose more general recommendation systems should be done. Because most current recommendation methods are heavily developed to focus on a particular problem domain, they are not easily transferable to other content or problem domains. Second, numerous recommendation methods have been proposed which are impossible to compare with methods deployed on a commercial scale. However, most of them have the initiative aims to apply new technology or some concepts. It means they have started their research not from the view of the recommendation system, but from the view of the available technologies or concepts. This fact could lead to research bias potentially because of researcher's belief on technologies they keep in mind. Hence, the method to verify recommendation system itself is needed and it should be distinguished a simple accuracy metric. Third, existing developed recommendation system are mostly based solely on historical rating data and recommend the most similar one to what they chose in the past. However, there are different kinds of cases in real world. For example, in case of lunch menu recommendation, people's preference can be affected by weather, their mood, and so on rather than their original preference.

Fourth, all of current recommendation systems only recommend what people would like to. However, when people make a decision, sometimes not-recommend list is very important. It is obviously valid and influenced their decision. Hence, to develop a recommendation system which suggests not-recommend list would be very useful. Fifth, today's recommendation systems are overall lack robustly developed personalized services. For example, user's current context data such as location, activity and social context are not sufficiently considered. A novel approach to personalization that addresses users' privacy concerns is a critical area of future research. That is because context-aware technologies have been developed dramatically over the last decade and privacy issues are a major consideration for more wide scale implementations.

As a conclusion, we expect these implications stated above can suggest useful directions to researchers for a future recommendation system development and give some insights or tips to recommendation system developers to develop new system or to improve their system.

5. Conclusion

As e-commerce grows, recommendation systems are widely used to help deal with the problem of information overload. People are often overwhelmed with the number of options available to them. To combat this information overload, many have turned to recommender systems. Moreover, ubiquitous computing environment settings aim to empower the services enough to proactively respond the requests of the individuals who are located in a certain physical space. It means that ubiquitous services require more than networked displays, devices and sensors; it relies implicitly on recommendation systems which either directly serve the user or provide users with critical services to some other applications.

In this paper, we have performed an analysis for recommendation systems along four different key dimensions : their domain, their objective, their underlying method, and their method of evaluation of recommendation systems. And then on the basis of the result, we provide systemic review and present some basic issues on improvement action. Moreover, we also find useful implications on recommendation system and give some ideas to recommendation system developers to improve their system.

Finally, our analysis could contribute to understand the overall development trend of recommendation system and to seek adequate and relevant research topics. We expect this research would be a reference source to researchers and developers who are related to this area or interested in recommendation system.

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Abstract

추천시스템 연구의 개발추세 동향

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추천시스템은 정보 과부하의 문제를 해결하기 위해 폭넓게 사용되어지고 있다. 지난 수십년 동안 다양한 추천시스템이 정보량이 그것을 처리할 수 있는 능력보다 더 빠르게 증가하게 됨에 따라 개발되어져 왔다. 이 같은 상황에서 본 연구의 목적은 기 개발된 추천시스템을 분석하여 시스템적 관점을 제공하고 이를 구현하는데 따르는 기본적인 이슈들을 밝히는 것이다. 이를 통하여 추천시스템의 개선을 위한 유용한 정보를 제안하며, 시스템 개발자들에게는 그러한 시스템을 개선하기 위한 아이디어를 제공하고자 한다. 특히 본 연구는 추천시스템의 이론적 관점에 집중하는데, 이를 위해 과거 추천시스템의 도메인과 목표, 주요 방법 및 평가 방법에 대해서 다루고자 하며, 이 결과는 통계치나 도표 등의 형태로 보이려고 한다.

Keywords : 추천시스템, 메타분석, 추세분석

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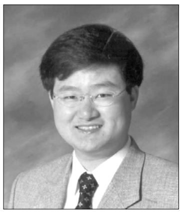
저 자 소 개

이연님
현재 경희대학교 국제경영학과 박사과정에 재학중이며 동시에 유비쿼터스 비즈니스&서비스 연구센터(RCUBS ; Research Center for Ubiquitous Business and Services)에서 연구원이다. 2000년에 한동대학교 경영경제학부에서 학사, 2003년 이화여자대학교에서 석사학위를 취득하였다. 석사학위 취득 후 4년간은 금융권과 IT 컨설팅 분야에서 IT컨설턴트로 활동했으며, 현재는 RCUBS에서 연구원으로 일하면서 정보통신부 과제와 서울시 과제에 참여하고 있다. 관심 연구분야는 상황인식 기술, 유비쿼터스 서비스내 프라이버시 이슈 등이다.



권오병
2004년부터 경희대학교 국제경영학부에 재직 중이다. 1995년에 한국과학기술원에서 박사학위를 취득하였으며 1996년부터 2003년까지 한동대학교 경영경제학부 교수로 재직한 바 있다. 2002년에는 미국 카네기멜론대학 전산학부에서 유비쿼터스 시스템인 MyCampus 프로젝트에서 시맨틱 웹, 다중에이전트 및 추론시스템을 공동으로 구축한 바 있다. 현재는 경희대학교 내 유비쿼터스 비즈니스&서비스 연구센터장으로서 여러 정부 과제를 수행하고 있다. 관심 연구분야는 다중에이전트 시스템, 상황인식 기술, 의사결정지원시스템 등이다.